Bad Beta Good Beta, State-space News Decomposition and the Cross-section of Stock Returns

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Abstract

This study employs an innovative market-based approach, where ROE are employed as proxy for cash-flow news and a state-space model is used for market news decomposition. We document that the explanatory power of the Bad Beta Good Beta (BBGB) model of Campbell and Vuolteenaho (2004) is about 30% for the cross-section of stock returns. We also find the BBGB model adequately explains the size effect leading to its superior performance. The results are obtained controlling for news decomposition method and market news proxies bias. We contribute to the literature by providing an alternative easy-to-implement and consistent market-based method for news decomposition.

1. Introduction

Explaining cross-sectional differences in equity market returns is one of the great challenges of modern finance, and it has been the subject of asset pricing research for decades. Theoretical models, such as the capital asset pricing model (CAPM) of Sharpe (1964), Lintner (1965) and Black (1972), the intertemporal CAPM of Merton (1973), the consumption CAPM of Breeden (1979), and subsequent related studies shed insight on this issue and initially won broad support from academics. However, a special challenge for asset pricing is the stochastic factors of the data generation which researchers cannot control experimentally. During the 1980s and 1990s, several deviations from the CAPM, or "anomalies", were discovered by researchers, i.e., the *size effect* reported by Banz (1981) and Fama and French (1992), the *value effect* discovered by Basu (1983), Rosenberg et al. (1985) and Fama and French (1992), and the *momentum effect* documented by Jegadeesh and Titman (1993). These stylized facts fail to fit the established theories and render those theoretical models unsuitable. For instance, Fama and French (1992) find that the market data does not appear to support the pricing of systematic risk indicated by CAPM, Karathanasis et al. (2010) argue that the static structure imposed on the CAPM might have been the reason behind the rejection of the model and the inconsistency between equity returns and estimated systematic risk, and Breeden et al. (1989) find weak support for consumption CAPM in the market.

Empirically, Fama and French (1993) claim that some practical factors can describe the characteristics of stocks well and propose the now famous three-factor model. There followed an enormous amount of empirical research that attempted to find these powerful empirical factors. Carhart (1997) introduces the fourth momentum factor and finds it boosts the model's explanatory power. O'Brien et al. (2010) confirm further the existence of a significant positive average relation between momentum and returns in Australia. Chan et al. (2011) show that the default risk asset-pricing factor (DEF) has a complementary role to small minus big and high minus low in a four-factor version of Fama-French model. On examining the cross-sectional determinants of post-IPO long-term stock returns in China, Chang et al. (2010) document that the aftermarket P/E ratio has the most robust negative association with post-IPO stock returns. Underwriter reputation has a positive effect on post-IPO stock returns, while board size has a negative impact. In more recent work, Cremers et al. (2011) provide strong evidence that aggregate stock market volatility and aggregate jump risk are both priced risk factors. However, jump risk appears to be economically less important and statistically less significant than volatility risk. Docherty et al. (2011) show that asset tangibility is priced in the cross-section of equity returns, and this relationship is most evident in the materials industry, which is characterized by irreversible, firm-specific assets. These results persist after controlling for the Fama and French (1992) factors.

Although, these factor models show superiority in fitting the cross-section of stock returns, Gharghori et al. (2009) conclude that its performance is less than satisfactory in Australia. Campbell (2000) also argues that they provide no theoretical foundation and the factors are chosen atheoretically to fit the empirical evidence. So, financial economists sought to construct a theory-motivated model that is good at capturing the cross-sectional characteristics of stock returns. Campbell and Vuolteenaho(2004) propose a two-beta ICAPM (TBI) model and claim that size and value anomalies can be satisfactorily explained with their theoretical framework and that the TBI model outperforms CAPM in cross-sectional explanation, i.e., in the 1963-2001 period, the explanatory power of the TBI model is up to 49.26% compared to that of 3.10% of the traditional CAPM. [1] In their framework, Campbell and Vuolteenaho break down the original CAPM beta of a stock with a market portfolio into two components: the first, cash-flow beta, reflects the risk of market future cash flows, and the second, discount-rate beta, reflects the risk of market future discount rates. They point out that cash-flow beta is related to long-run risk with a higher market price and discount-rate beta is related to short-run risk with a lower market price. From this perspective, they name them bad beta and good beta, respectively, and argue that the risk of a stock is determined not by the stock's overall beta with the market but by its bad cash-flow beta with a secondary influence from its good discount-rate beta. The two-beta ICAPM model is therefore called the BBGB (bad beta, good beta) model. In order to implement decomposition, Campbell and Vuolteenaho use a vector autoregressive (VAR) method, which is introduced by Campbell (1991).

[1] Refer to Equation (9) of Campbell and Vuolteenaho(2004), page 1263, and Table 7 of Campbell and Vuolteenaho(2004a), page 1267.

Despite the merits of Campbell and Vuolteenaho (2004) framework, Chen and Zhao (2009) point out that the decomposition of cash-flow news and discount-rate news based on Campbell and Vuolteenaho's VAR method is unreliable. They find the empirical results are not robust, i.e., a small, reasonable change in the state variable choices of the VAR method may overturn the original findings. Bianchi (2010) also documents a strong dependence of Campbell and Vuolteenaho's empirical results on the sample selection. He find that the BBGB model can explain 50% of the cross-sectional variations in the 1963-2001 period only if the 1929, 1930 and 1931 year data are also included in the sample when using VAR for news decomposition, Otherwise the explanatory power drops almost to 0%. These problems cast doubts on the reliability of Campbell and Vuolteenaho's empirical findings.

Given these arguments, this study aims to gain insights in the performance of the BBGB model in explaining the cross-section of stock returns. Since arguments focus on news decomposition, we use two market-based methods, which avoid the use of the controversial VAR method, to construct the measures of cash-flow news and discount-rate news series in testing the BBGB model. The first method uses the discounted sum of accounting ROE as a proxy for cash flows and combines it with a theory-motivated state-space model to separate discount rates from the realized market returns; the second method employs ROE and P/E ratios directly as market-based measures for cash-flow news and discount-rate news. Our results show that the explanatory power of the BBGB model for the cross-section of stock returns is about 30%; that the BBGB model performs better with the first method than with the second method, and that both of them outperform the traditional CAPM in explaining the cross-sectional variations of stock returns.

This work is a substantial contribution to the current body of research. First, our study confirms the superior performance of the BBGB model in explaining the cross-section of stock returns from the market perspective. Our results indicate that the real explanatory power of the BBGB model for the cross-sectional variations of stock returns is between 20% and 30%. Although lower than reported in Campbell and Vuolteenaho (2004), it indeed outperforms results using the CAPM. We also prove that the BBGB model can explain the size effect and this leads to its outperformance in the cross-section of stock returns. This is very important as the BBGB model provides theoretical accommodation for one of the most noticeable cross-sectional stock return anomalies in the literature. Second, we proposed a direct market-based method in news decomposition that is proved to be consistent and efficient. Specifically, we construct an ICAPM-based state-space model for market news decomposition. The merits of our method include a greatly improved quality of information extraction. Campbell et al. (2010b) argue that "realized returns of the stocks will be inherently noisy and if a meaningful financial model such as ICAPM can be used in extracting information from realized stock returns, such noise can be efficiently reduced". Our method also has econometric and information advantages compared to the VAR method which induce skepticism of results, as according to Binbergen and Koijen (2009), state-space models aggregate the whole historical information from the full sample in order to obtain the estimations of future returns while the first order VAR model used in Campbell and Vuolteenaho (2004) normally only relates the future returns with past information over one lag.

The remainder of the paper is organized as follows. Section 2 details the methodologies we used. Section 3 presents the empirical findings, and Section 4 provides related discussions for the results. Finally, Section 5 concludes.

2. Methodology

We propose two alternative market-based approaches to construct proxies for the market cash-flow news and discount-rate news. There are two major advantages in our framework: i) we avoid using the controversial VAR news decomposition method; and ii) it provides more direct information from the market. Thus the results will be impartial for theoretical arguments. Both of our proposed market-based methods are set up controlling for the market news decomposition method and news proxies bias which are central to the debate.

2.1 Empirical Method #1: ROE+SSP

2.1.1 Market Cash-flow News

We use market-level accounting ROE to proxy market cash-flow news. Cohen et al. (2003, 2009) and Campbell et al. (2010a) argue for the use of the discounted sum of ROE as a good measure of cash flow fundamentals. Thus, we follow their specification and compute the measure as

$$N_{CF,t+1} = 1/10^{*} \sum_{k=1}^{K} \rho^{k-1} roe_{M,t+k} \quad (1)$$

where $N_{CF,t+1}$ is the measure of market cash-flow news at time t+1, and $roe_{M,t+k}$ is log return on equity. Since cash-flow news reflects long-term trends rather than short-term fluctuations, it is reasonable for the horizon, K, to take a value of 60 (12 months x 5 years). The correct way to adjust profitability for inflation is unclear so we adopt Campbell et al.'s (2010a) method. Hence

$$roe_{M,t+k} = \log(1+\mathrm{ROE}_{M,t+k}) - 0.4^{*}\log(1+y_{t+k}) \quad (2)$$

where, by Ross et al. (2006), $\mathrm{ROE}_{i,t+k} \equiv NI_{i,t+k}/TCE_{i,t+k}$, that is the net income of stock i at time $t+k$ on its total common equity and y_{t+k} is the Treasury Bill rate with 3 months maturity at time $t+k$. This approach ensures that our measure of real profitability is orthogonal to variations in the nominal interest rate during our sample period.[2]

Once we have the return on equity of an individual stock, $\mathrm{ROE}_{i,t+k}$, we calculate the value-weighted market return on equity, $\mathrm{ROE}_{M,t+k}$, and then use the *cubic spline*

[2] Refer to Campbell et al. (2010a) page 318.

interpolation method to transform quarterly $\mathrm{ROE}_{M,t+k}$ into a monthly data series. Thus, we use Equations (1) and (2) to construct a proxy for market-level cash-flow news. We still need an econometric method to separate discount-rate news based on Equation (1) in Campbell and Vuolteenaho (2004). Chen and Zhao (2009) show that the decomposition of cash-flow news and discount-rate news based on the VAR method in Campbell and Vuolteenaho (2004) is unreliable as they find Campbell and Vuolteenaho's empirical results are sensitive, i.e., a small reasonable change in the state variable choices of the VAR method may overturn the original findings. Bianchi (2010) also points out that this VAR method is sensitive to the choice of information samples. He argues that different samples will cause structural changes in the estimation of the coefficients of the state variables in the VAR system, in turn causing structural changes in the separated market news through the change of coefficient matrix of the state variables. In light of this, we propose a totally different method for market news decomposition: decomposition based on a *state-space* method. This provides two main advantages. First, by applying this state-space method, we may base news decomposition on a meaningful pricing model such as the ICAPM. Campbell et al. (2010b) suggest that realized stock returns contain a certain amount of noise. As a result, if a meaningful asset pricing model (such as ICAPM) can be applied in extracting information from realized stock returns, this noise effect can be effectively reduced to improve the quality of information. Second, as pointed out in Binsbergen and Koijen (2009), the state-space method aggregates information from the full historical sample to generate forecasts for the future. This clearly has an information advantage over the first order VAR model used in Campbell and Vuolteenaho (2004) which usually relates future forecasts to lag one information only.

2.1.2 State-space Model Construction

2.1.2.1 A State-space Framework

In order to set up the state-space framework, we first need to identify the relationships between observations (prices, returns) and state variables (observable and latent factors). They are crucial for the identification and estimation of the latent factors and parameters with which we are concerned.

We introduce a proxy for $N_{CF,t+1}$. Specifically, we modify Equation (1) such that

$$\widetilde{N}_{CF,t+1} = 1/10 * \sum_{k=1}^{K} \rho^{k-1} roe_{M,t+k} \tag{3}$$

where $\widetilde{N}_{CF,t+1}$ is a measure for the market level cash-flow news. We specify the relation between $N_{CF,t+1}$ and $\widetilde{N}_{CF,t+1}$ as

$$N_{CF,t+1} = \widetilde{N}_{CF,t+1} + \zeta_{t+1} \tag{4}$$

where ζ_{t+1} is measurement error. Equation (4) is the first measurement equation.

Based on Campbell (1993) and Campbell and Vuolteenaho (2004), Maio (2009) derives the relation between the pricing kernel and market information as

$$m_{t+1} = E_t(m_{t+1}) - \gamma N_{CF,t+1} + N_{DR,t+1} \tag{5}$$

where $m_{t+1} = \log(M_{t+1})$, which is the pricing kernel. $N_{DR,t+1}$ is the measure of market discount-rate news at time t+1, and γ denotes relative risk aversion coefficient. Then Maio (2009) expands the equilibrium asset pricing model $1 = E_t(M_{t+1}R_{i,t+1})$ by the second order Taylor expansion as

$$E_t(r_{i,t+1}) - r_{f,t+1} + 0.5Var_t(r_{i,t+1}) = - Cov_t(m_{t+1}, r_{i,t+1}) \quad (6)$$

If we change the subscript i into market portfolio M and substitute Equation (1) in Campbell and Vuolteenaho (2004) and Equation (5) into Equation (6), we get

$$E_t(r_{M,t+1}) - r_{f,t+1} + 0.5Var_t(N_{CF,t+1} - N_{DR,t+1} + E_t(r_{M,t+1}))$$
$$= - Cov_t[E_t(m_{t+1}) - \gamma N_{CF,t+1} + N_{DR,t+1}, N_{CF,t+1} - N_{DR,t+1} + E_t(r_{M,t+1})] \quad (7)$$

where the M is market portfolio, and m is the pricing kernel. Under the *homoscedasticity* assumption by Campbell (1993) and Campbell and Vuolteenaho (2004), we can write Equation (7) as

$$E_t(r_{M,t+1}) - r_{f,t+1} + 1/2(\sigma_{CF}^2 + \sigma_{DR}^2 - 2\sigma_{CF,DR})$$
$$= \gamma\sigma_{CF}^2 - \gamma\sigma_{CF,DR} - \sigma_{CF,DR} + \sigma_{DR}^2 \quad (8)$$

Further manipulations give the expressions of expected market return as

$$E_t(r_{M,t+1}) = r_{f,t+1} + \frac{1}{2}((2\gamma - 1)\sigma_{CF}^2 + \sigma_{DR}^2 - 2\gamma\sigma_{CF,DR}) \quad (9)$$

where $\sigma_{CF,DR}$ denotes the covariance between cash-flow and discount-rate news. Equation (9) is the second measurement equation.

2.1.2.2 State Space Representation

We now specify the dynamics of the state variables. Since the news are unlikely to be autocorrelated, we specify a MA(1) process for the latent factors, ε_t, such that

$$\begin{bmatrix} \varepsilon_{t+1} \\ \varepsilon_t \end{bmatrix} = \begin{bmatrix} 0_{2x2} & 0_{2x2} \\ I_{2x2} & 0_{2x2} \end{bmatrix} \begin{bmatrix} \varepsilon_t \\ \varepsilon_{t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{t+1} \\ 0 \end{bmatrix} \quad (10)$$

where $\varepsilon_t \equiv \begin{bmatrix} N_{CF,t} \\ N_{DR,t} \end{bmatrix}$. This specification determines the news to be uncorrelated with past news, but have a dynamic process to follow.

Then we set up a linear-Gaussian state-space system using

$$\mathbf{S}_{t+1} = \mathbf{F}\mathbf{S}_t + \mathbf{v}_{t+1} \qquad \text{(state equation)} \qquad (11)$$

$$\mathbf{y}_{t+1} = \boldsymbol{\alpha}_t + \mathbf{A}'\mathbf{S}_{t+1} \qquad \text{(measurement equation)} \qquad (12)$$

where state vector $\mathbf{S}_{t+1} = \begin{bmatrix} \varepsilon_{t+1} \\ \varepsilon_t \end{bmatrix}$, the initial value $\mathbf{S}_0 = [0\ 0\ 0\ 0]'$, $\mathbf{v}_{t+1} = [N_{CF,t+1}\ N_{DR,t+1}\ N_{CF,t}\ N_{DR,t}]'$, and the coefficient matrix $\mathbf{F} = \begin{bmatrix} 0_{2x2} & 0_{2x2} \\ \mathbf{I}_{2x2} & 0_{2x2} \end{bmatrix}$. The observation vector $\mathbf{y}_{t+1} = [r_{M,t+1}\quad N_{CF,t+1}]'$, of which $r_{m,t+1}$ means log value of market stock return, and $N_{CF,t+1}$ is measured by Equation (4). The coefficient matrix $\mathbf{A} = \begin{bmatrix} 1 & -1 & 0 & 0 \\ 1 & 0 & 0 & 0 \end{bmatrix}$, and the intercept term $\boldsymbol{\alpha}_t = [E_t(r_{M,t+1})\quad 0]'$. The variance-covariance matrix of latent variable ε_t can be written as $\Omega = \begin{bmatrix} \sigma_{CF}^2 & \sigma_{CF,DR} \\ \sigma_{CF,DR} & \sigma_{DR}^2 \end{bmatrix}$, where σ_{CF}^2, σ_{DR}^2 and $\sigma_{CF,DR}$ denote the variance of cash flows and discount rates, and the covariance of them respectively.

Under estimating，first-order updating follows Equation (11)，second-order updating is given by the parameter matrix where $\mathbf{P}_{1|0} = \begin{bmatrix} \Omega_{2x2} & 0_{2x2} \\ 0_{2x2} & \Omega_{2x2} \end{bmatrix}$, and the variance-covariance matrix of state variable $\mathbf{S}_{t+1}$ can be written as $var_t(\mathbf{S}_{t+1}) = \begin{bmatrix} \Omega_{2x2} & 0_{2x2} \\ 0_{2x2} & 0_{2x2} \end{bmatrix}$. We apply the MLE method including a Kalman filter to estimate this model and adjust the variance-covariance matrix of the estimated coefficient using White (1982) in order to get a robust standard error.

2.2 Empirical Method #2: ROE+P/E

We now look at the second method which provides proxies for cash-flow news and discount-rate news directly without using any separation model. This method is more direct and reduces the model specification error to a minimum. Following Campbell et al. (2010a), we use Equation (1) to proxy market cash-flow news, and monthly increments in the market's log P/E ratio to proxy market discount-rate news. We write

$$-N_{DR,t+1} = 1/10^{*} \ \sum_{k=1}^{K}[\rho^{k-1}\Delta_{t+k}\ln(P/E)_{M}] \tag{13}$$

where $-N_{DR,t+1}$ measures the negative market discount-rate news at time t+1, K equals 60 (12 months x 5 years), and Δ denotes the first-order difference. This construction is consistent with the findings of Campbell and Shiller (1988a, 1988b) and Campbell (1991), among others, that discount-rate news dominates cash-flow news in aggregate returns and price volatility.[3]

2.3 Data

2.3.1 Data Sources

We use monthly data from 1973 to 2006 in this study, subject to data availability. The data used to construct ROE is collected from the COMPUSTAT database with a quarterly frequency. We transform quarterly ROE into monthly data using the *cubic spline* interpolation method. Although ROE data is available from 1972, to reduce

[3] Refer to Campbell et al. (2010a), page318.

bias due to few companies included in earlier quarters, we ignore the first several quarters and begin our sample period from the third quarter of 1973. The ROE are based on calculations for individual stocks. We need to calculate the value-weighted market-level ROE. The market value data and the market return we use are from CRSP database. The monthly P/E data is taken from Robert J. Shiller's website.[4] We use the one month yield on the 3-month U.S. Treasury bill as the risk-free rate and all the data are collected for the same sample period of September 1973 to January 2006.

2.3.2 Cross-sectional Stock Portfolios

Daniel and Titman (1997) point out that it can be dangerous to test asset pricing models using only portfolios sorted by characteristics known to be related to average returns, such as size and value. Characteristics-sorted portfolios are likely to show some spread in betas identified as risk by almost any asset pricing model, at least in sample. When the model is estimated, a high premium per unit of beta will fit the large variation in average returns. Thus, at least when premia are not constrained by theory, an asset pricing model may spuriously explain the average returns for characteristics-sorted portfolios. To alleviate this concern, Campbell and Vuolteenaho (2004) follow the advice of Daniel and Titman (1997) and construct a second set of 20 risk portfolios apart from the original 25 *ME*- and *BE*/*ME*-sorted portfolios.

[4] We can download data from Shiller's website: http://www.econ.yale.edu/~shiller/data.htm

In this study, we use the same 45 stock portfolios to test the asset pricing model. The 25 *ME*- and *BE*/*ME*-sorted portfolios are from French's website and the 20 risk portfolios for the 1973:09-2001:12 period are supplied by Campbell and Vuolteenaho (2004). [5] Following the example of Campbell and Vuolteenaho (2004), we construct the extended sample from 2002:01 to 2006:01 of the 20 risk portfolios.

3. Empirical Results

3.1 Decomposed Cash-flow and Discount-rate News

(Insert Table 1 here)

Table 1 contains the estimated parameters of the state-space model for news decomposition and descriptions for the two types of market news that are estimated. From Table 1, in the 1973:09-2006:01 period, the relative risk aversion coefficient of the market is 27.78, which is very close to the estimation of 28.75 for the period of 1963:07-2001:12 of Campbell and Vuolteenaho (2004). The large positive relative risk aversion coefficient estimated is consistent with risk-return trade-off literature which require a positive risk aversion from classic asset pricing theories. It also complies with the theoretical need of the BBGB model that the market price of relative long-term risk, as measured by cash flow risk, should be higher than that of

[5] The data can be downloaded from the AER's website: http://www.e-aer.org/data/dec04_data_campbell.zip

the discount rate risk. From the estimated $\ln(\sigma^2_{dr})$ and $\ln(\sigma^2_{cf})$, we compute the variance of estimated discount-rate news to be about 0.102% per month, which is much higher than the 0.042% per month for cash-flow news. This suggests that discount-rate news dominates cash-flow news in aggregate market returns, consistent with the findings of Campbell and Vuolteenaho (2004) and Campbell (1991). Table 1 results also indicate that the correlation coefficient between the two market news is low again confirming the findings of Campbell and Vuolteenaho (2004).

One thing we need to make clear here concerns the predictable components contained in our discounted sums of ROE when using Equation (1) to construct the cash-flow news. Campbell et al. (2010a) conduct a robustness test and argue that the predictable components are purely mechanical, since their robustness test shows that the beta structure calculated by the two market news is stable and it is not driven by the predictable components.

(Insert Figure 1 here)

Figure 1 plots our proxies for the market's cash-flow news and discount-rate news over a forward-looking horizon of five years. There are some periods where both cash flows and discount rates pushed the stock prices in the same direction. For example in the early 1970s, late 1990s and mid-2000s, cash-flow news was positive and market discount-rate news decreased, pushing up market prices. However, there are also some periods where both influence market price pushing it in opposite directions. For instance in the late 1970s, from the late 1980s to early 1990s and in the early 2000s, cash-flow news was positive while discount rates were rising, and in the early 1980s cash-flow news was negative and discount rates were falling. Combining the two sections of the figure, we observe the dynamic interaction between the two market news components which lead to the realization of the market return process. The relative smoothness of the cash-flow news series confirms that the variation of the cash-flow news is less than that of the discount-rate news but with stronger persistence. This is consistent with the theoretical explanation from Campbell and Vuolteenaho (2004) that cash-flow news is related to the long-term trends rather than short-term fluctuations of the stock market.

3.2 Regression Formula for Asset Pricing Model

In empirical tests, the theoretical model of the two–beta ICAPM can be written as

$$\bar{R}_i^e = g_0 + g_1\hat{\beta}_{i,CF_M} + g_2\hat{\beta}_{i,DR_M} + e_i \tag{14}$$

where $\bar{R}_i^e \equiv \bar{R}_i - \bar{R}_{rf,}$ which denotes the sample average excess return of stock i. The relative risk aversion coefficient $\hat{\gamma} \equiv g_1/g_{2,}$ and following Campbell and Vuolteenaho (2004), $\hat{\beta}_{i,CF_M}$ and $\hat{\beta}_{i,DR_M}$ can be calculated as

$$\hat{\beta}_{i,CF_M} \equiv \frac{\widehat{cov}(r_{i,t}, \hat{N}_{CF,t})}{\widehat{Var}(\hat{N}_{CF,t} - \hat{N}_{DR,t})} + \frac{\widehat{cov}(r_{i,t}, \hat{N}_{CF,t-1})}{\widehat{Var}(\hat{N}_{CF,t} - \hat{N}_{DR,t})} \tag{15}$$

$$\hat{\beta}_{i,DR_M} \equiv \frac{\widehat{cov}(r_{i,t}, -\hat{N}_{DR,t})}{\widehat{Var}(\hat{N}_{CF,t} - \hat{N}_{DR,t})} + \frac{\widehat{cov}(r_{i,t}, -\hat{N}_{DR,t-1})}{\widehat{Var}(\hat{N}_{CF,t} - \hat{N}_{DR,t})}. \tag{16}$$

These beta estimators deviate from the usual regression-coefficient estimator by adding a lag. This is motivated by the possibility that, especially during the early years of our sample period, not all stocks in our test-asset portfolios were traded frequently and synchronously. If some portfolio returns are contaminated by stale prices, market return and news terms may spuriously appear to lead the portfolio returns, as noted by Scholes and Williams (1977) and Dimson (1979). In addition, Lo and MacKinlay (1990) show that the transaction prices of individual stocks tend to react in part to movements in the overall market with a lag, and the smaller the company, the greater the lagged price reaction. McQueen et al. (1996) and Peterson and Sanger (1995) show that these effects exist even in relatively low-frequency data (i.e., those sampled monthly). These problems are alleviated by the inclusion of the lag term.

For the static CAPM, we use the standard form

$$\bar{R}_i^e = \alpha_0 + \alpha_1 \hat{\beta}_{i,M} + u_i \quad (17)$$

where $\bar{R}_i^e$ is the same as Equation (14). We perform the same lag one adjustment to $\hat{\beta}_{i,M}$ in order to alleviate any potential problems with infrequent trade and asynchronous trade. Thus

$$\hat{\beta}_{i,M} \equiv \frac{\widehat{cov}(r_{i,t}, r_{M,t})}{\widehat{Var}(r_{M,t})} + \frac{\widehat{cov}(r_{i,t}, r_{M,t-1})}{\widehat{Var}(r_{M,t})} \quad (18)$$

The monthly return data of individual stocks are taken from the CRSP database.

3.3 Testing Results

(Insert Table 2 here)

Table 2 reports results from using the BBGB model and the CAPM for the sample period 1973-2006. The first set of 3 rows corresponds to the zero-beta rate (in excess of the treasury-bill rate), the second set to the premium on cash-flow beta, the third set of 3 rows to the premium on discount-rate beta, and the fourth set of 3 rows to the premium on CAPM market beta. Within each set, the first row reports the point estimate in fractions per month, and the second row provides an annualization for it, multiplying by 1,200 to ease the interpretation of the estimate. The third row presents the standard error of the monthly estimate. The near-zero standard errors associated with the estimation suggest the parameters are adequately estimated.

Below the premia estimates, we report the R-squared statistic for a cross-sectional regression of average returns on our test assets onto the fitted values from the model. The regression $\widehat{R}^2$, following Campbell and Vuolteenaho (2004), is computed as $\widehat{R}^2$ = 1- RSS/RSM, where RSS is the residual sum of squares and RSM is the residual sum of squares when only the constant is used as a regressor. Table 2 shows that in the 1973-2006 period, the cross-sectional $\widehat{R}^2$ statistic is about 21% for the BBGB model based on method one. It outperforms the traditional CAPM, which explains only 10.68% of the cross-section of stock returns. The explanatory power of the BBGB model based on method two is around 19% which is also better than the CAPM result. The reported results in Table 2 confirm the effectiveness of the two proxies in capturing the two types of market news to explain the cross-sectional variations. A slightly better performance for the first empirical method indicates that the state-space method we propose, despite the modeling and estimation bias, can outperform a direct proxying method as well as established asset pricing models.

(Insert Table 3 here)

The small-growth portfolio among the 45 portfolios we used in cross-sectional testing is well known to present a particular challenge to asset pricing models. For example, the three-factor model of Fama and French (1993) does not fit this portfolio very well. Recent research on small-growth stocks by Lamont and Thaler (2003), Mitchell et al. (2002), D'Avolio (2002), and others suggest that the pricing of some small-growth stocks is materially affected by short-sale constraints and other limits to arbitrage. This may help explain the unusual behavior of the small-growth portfolio. Hence Table 3 shows the new estimate results for the BBGB model and CAPM. The test assets are the 24 ME- and BE/ME-sorted portfolios (the first small-growth portfolio excluded) and the 20 risk-sorted portfolios. The results indicate that the explanatory power of the BBGB model using method one for news decomposition and the CAPM increases to 29.54% and 18.67%, respectively. The explanatory power of the BBGB model using method two for news decomposition rises a little to 23.10%. These increases in explanatory power demonstrate that the behavior of the small-growth stock portfolio is, indeed, very special and not easy for the established asset pricing models to explain. The lower increase for the second method suggests that a purely market-based method is affected less by the exclusion of the small-growth portfolio, reflecting the sensitivity issues faced by model-based methods when confronted with the small-growth portfolio. Going one step further, it also strengthens our previous results that the BBGB model performs slightly better with method one than with method two, which outperforms the traditional CAPM, in explaining the cross-section of stock returns. Based on these findings, we argue that the explanatory power of the BBGB model for the cross-section of stock returns lies between 20% and 30%, but is not as high as the 49% reported in Campbell and Vuolteenaho (2004). The BBGB model with market-based approaches for news decomposition outperforms the traditional CAPM in explaining the cross-section of stock returns. This is consistent with Campbell and Vuolteenaho (2004). To show its effectiveness, a robust news decomposition method, like the state-space method, should be applied. The BBGB model based on the state-space method for news decomposition (ROE+SSP) outperforms those based on direct proxies for market cash-flow and discount-rate news (ROE+P/E). The advantage of the state-space method is even more obvious when one takes the cost of information acquisition into account as a better result is obtained with less market information input i.e., we need market cash-flow information only in the state-space method.

3.4 BBGB and Size Effect

Through further examination, we also find that the superior performance of the BBGB model in cross-section explanation lies in its ability to accommodate the *size effect*. In earlier research, the size effect is referred to as the cross-section anomaly where small-sized stocks tend to have higher average returns than large-sized stocks, this cannot be justified by their market betas. As a result, factor models which include the size factor will have better incremental cross sectional explanatory power over models that only rely on market betas. The BBGB model that suggests the market cash-flow beta will have a higher market price of risk than will market discount rate beta. So if small-sized stocks tend to have higher cash-flow betas then it is possible that the BBGB theory can provide an explanation for the on-average higher returns for small stocks. In order to see this, we compute cash-flow beta and discount-rate beta for the 25 ME- and BE/ME- sorted portfolios based on the robust empirical methods we proposed earlier. The beta estimation results are reported in Table 4 and Table 5.

(Insert Table 4 here)

Table 4 reports the estimated betas for the 25 size- and book-to-market portfolios over the 1973:09-2006:01 period. The portfolios are organized in a square matrix with growth stocks to the left, value stocks to the right, small stocks on the top, and large stocks at the bottom. Along the bottom of the matrix we report the beta differences between the smallest and largest portfolios in each BE/ME category. The upper panel displays cash-flow betas, while the lower panel displays discount-rate betas. In the sample period, small stocks have higher bad cash-flow betas and good discount-rate betas than large stocks. Since the risk price of cash-flow betas is higher than that for discount-rate betas, [6] the BBGB model suggests that small stocks have much higher average returns simply because they have bigger bad cash-flow betas in the market beta. On the other hand, if cash-flow beta and discount-rate beta were added up to derive the single market beta, such a single market beta will give equal pricing weight for the two components i.e., bad beta and good beta. With equal pricing weight, the single CAPM beta will be unable to accommodate the size effect.

Hence, the BBGB model can justify the much higher average returns of small portfolios than that of large portfolios while the CAPM beta cannot.

(Insert Table 5 here)

To complete our investigation, we also compute the betas for the 25 ME- and BE/ME-sorted portfolios using the direct proxying method. Table 5 reports the results from our calculations. The negative difference between the small and large portfolios' discount-rate betas suggests the size anomaly is more acute than that observed in Table 4. This is due to the P/E ratio being used as the discount-rate proxy in this method while we applied the state-space method for discount-rate news in method one. From Table 5, we see that small stocks have even higher bad cash-flow betas and lower good discount-rate betas than large stocks when compared to previous results.

[6] The BBGB model suggests bad beta has γ times the market price than the good beta. We estimate γ to be 27.78 while Campbell and Vuolteenaho (2004) report a similar value of 28.75.

Since the risk price of cash-flow betas is about 28 times higher than that for the discount-rate betas, the BBGB model still justifies the much higher average returns of small portfolios than that of large portfolios. Thus we confirm that the BBGB model has an incremental ability over single market beta to accommodate the size effect and that this may lead to its superior performance in explanation of cross-sections.

4. Discussion

4.1 Robust Check for News Measures

The treatment of market cash-flow news and discount-rate news is a key concern. The two empirical methods we applied both aim to provide adequate proxies for the two types of market news. Empirical findings thus depend on the accuracy of such proxies. This is especially the case for the second empirical method when ROE and the P/E ratio are employed directly as market-based proxies. Although we believe the two market-based proxies are of economic meaning and empirical popularity, there is still need for robustness checking. In doing so, we make some adjustments to the original proxies' construction based on the properties of the two type of news. This adjustment will test the sensitivity of the results obtained to any change in information proxies. Specifically, as we argue that cash-flow news is a reflection of the market long-term trends, while the discount-rate news is a reflection of short-term market fluctuations, thus we adjust the 5-year forward-looking horizon, i.e., 6 years, for the ROE construction to reflect an even longer-term trend. Conversely we as well safely shrink the original horizon for the discount-rate news construction to shorter durations, i.e., 4 years or 3 years, to more adequately match the short-term market fluctuations. Thus the robustness tests are based on the extension and shrinkage of the original horizon of 5 years for cash-flow news and discount-rate news proxies, respectively, and the results show that the original findings are consistent. Therefore, our conclusions based on the empirical results are both confirmed as correct and robust.[7]

4.2 Robust Check for News Decomposition Method

In the section 2.1.2, we derive an expression for the expected market returns, i.e., Equation (9), under the homoscedasticity assumption of Campbell and Vuolteenaho (2004). From the forecast perspective, one may argue to use a non-constant term as the expectations of future market returns. In response to this, we propose a new estimation method that allows for time-varying variances for news decomposition. Such alternative also serves as measures for controlling for the method biases from the state-space model we proposed in the market news' decomposition. Specifically, we use the discounted sum of ROE for future 5 years to measure the cash-flow news. Then, based on Scruggs (1998), we estimate ICAPM of which the market variances follow a bivariate EGARCH-in-mean process to get the unexpected excess market returns. Thus the market discount-rate news can be backed out by Equation (1) in

[7] The robust test results are available from the author on request.

Campbell and Vuolteenaho (2004) with the derived two parts mentioned above. Finally, we find that the empirical test results based on this alternative news decomposition framework generally confirm the results obtained from using the state-space method and it provides supporting evidence for the cross-sectional explanatory power of the BBGB model.[8]

4.3 Relationship with Existing Works

In this study, we start our work based on Campbell and Vuolteenaho (2004) and draw inspiration from Chen and Zhao (2009), Bianchi (2010), Campbell et al. (2010a) and Binsbergen and Koijen (2009). Campbell and Vuolteenaho (2004) provide our research with motivation and a methodological framework. As we discussed, the intention of this study is to examine the performance of the BBGB model from a market-based perspective while controlling for various empirical issues including news decomposition and approximation. Our results provide market-based evidence for the debate over the empirical performance of the BBGB model. Relating our results to existing works, we find the following comparisons.

First, Campbell and Vuolteenaho (2004) test the explanatory power of the BBGB model for the cross-sectional 45 stock portfolios. We do the same in our work although the sample periods for ours are more up to date. Second, in calculating the

[8] The robust test results are available from the author on request.

cash-flow beta and discount-rate beta for the 1963-2001 period, Campbell and Vuolteenaho (2004) employ a much bigger information sample of 1928-2001 to decompose market news using the VAR method, and then extract the sub-sample (1963-2001) news to estimate the two betas. In our work, we proxy cash-flow news and discount-rate news directly using accounting variables, such as ROE and P/E. We believe that direct market-based information is more related to stock market reality, and that results gained using these market-based variables to test asset pricing models can better reflect a more market-based performance for the cross-sectional portfolios of the stock market. Third, Campbell and Vuolteenaho (2004) argue that the BBGB model far outperforms the CAPM in explaining the cross-section of stock returns. Our results confirms that the BBGB model has a better performance in this area than the traditional CAPM, while the market-based explanatory power is between 20% and 30%, which is lower than Campbell and Vuolteenaho (2004) who found it to be 49.26%. One reason why our results cannot match those of Campbell and Vuolteenaho (2004) lies in the difference in information extraction. But it can be easily demonstrated that Campbell and Vuolteenaho (2004), although using a longer information sample (1928-2001), do not yield comparable asset pricing test results due to the sensitivity the VAR method has to the information sample selection.

5. Conclusion

This study test the BBGB model using two market-based approaches for news decomposition in order to understand its true performance in explaining the cross-section of stock returns. This helps us avoid the use of the controversial VAR method while identifying direct evidence from the market. Our results show that the explanatory power of the BBGB model for the cross-section lies between 20% and 30%, lower than reported by Campbell and Vuolteenaho (2004). The BBGB model has better performance with the state-space method than with the direct proxy method, and both of them outperform the traditional CAPM in explaining the cross-sectional variations of stock returns. The robustness tests confirm that our conclusions are consistent and robust to news measurement biases and decomposition methods.

The solid results indicate that the high explanatory power of the BBGB model for the cross-section of stock returns in Campbell and Vuolteenaho (2004) may not be supported by the market-based evidence. However, the usefulness of the BBGB model is confirmed by using a state-space method for news decomposition, which helps to reestablish the advantage of Campbell and Vuolteenaho's theory over the CAPM in cross-sectional explanation. This is an important step in the search for a theory that can explain cross-sectional stock return variations. Further investigation also finds that the BBGB model can accommodate the size effect very well, providing insight in the superiority of the theory over CAPM.

The state-space method we use also broadens the empirical applications for market news decomposition theory. Because this method does not involve the state variables' choices needed in the VAR model, and the market news decomposition can be broadly carried out without considering whether certain periods must be included or excluded from the sample. For example, except for the United States, most countries have not experienced great depression like the one in the 1930s. Therefore, compared with the VAR model, our state-space method paves the way for the application of the BBGB model in different financial markets around the world.

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Table 1 State Space Model Estimate

Parameters	$ln(\sigma^2_{cf})$	$ln(\sigma^2_{dr})$	*corr*	γ
Estimate	-7.7628	-6.8917	0.2376	27.7806
S.E.	(0.0551)	(0.0421)	(0.0321)	(8.8703)
Likelihood	1.1849e+003			

Notes: The table shows the estimate statistics of the state-space model and the properties of cash-flow news and discount-rate news. $ln(\sigma^2_{cf})$ is log value of the variance of cash flows, $ln(\sigma^2_{dr})$ is log value of the variance of discount rates, *corr* means correlation coefficient, and γ is the relative risk aversion coefficient. The standard error is in the parentheses. Estimates are for the 1973:09-2006:01 period.

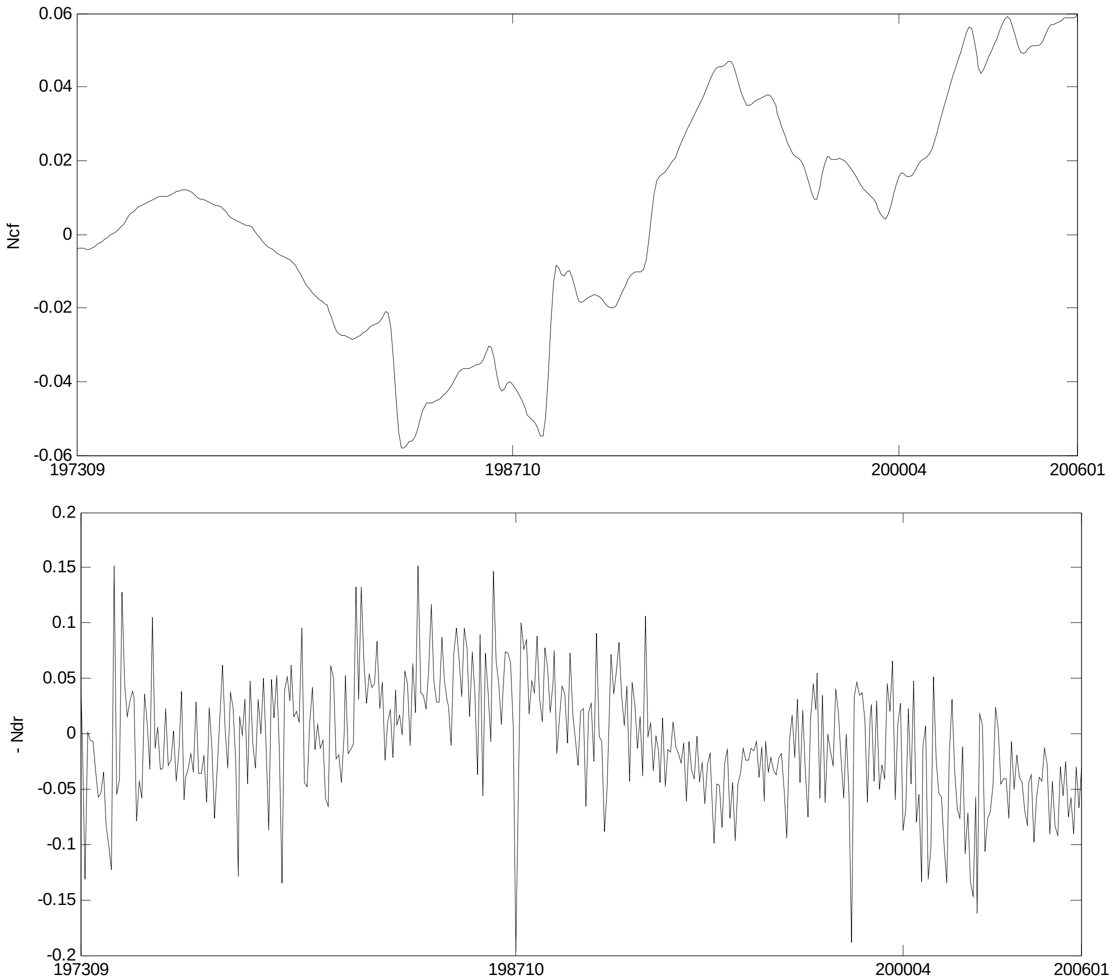

Figure 1 Cash-flow news and discount-rate news

Notes: The upper part is the curve of cash-flow news, which is the discounted sum of accounting roe with forward looking for 5 years (refer to Equation (1)). The lower part is the curve of discount-rate news, which is separated by state-space model from the realized market returns. Estimates are for the 1973:09-2006:01 period.

Table 2 Asset Pricing Tests for the Sample: 1973:09-2006:01

Model	**BBGB**	**BBGB**	**CAPM**
Method	[roe5+SSP]	[roe5+ P/E5]	[standard]
Intercept (g_0)	0.0068	0.0089	0.0059
% per annum	8.17%	10.62%	7.05%
Std.err.	(0.0000)	(0.0000)	(0.0000)
$\hat{\beta}_{CF}$ premium (g_1)	0.0241	0.0187	
% per annum	28.95%	22.46%	
Std.err.	(0.0000)	(0.0000)	
$\hat{\beta}_{DR}$ premium (g_2)	0.0021	0.0013	
% per annum	2.57%	1.56%	
$\hat{\beta}_{CAPM}$ premium (g_3)			0.0029
% per annum			3.52%
Std.err.			(0.0000)

$\hat{R}^2$	20.97%	19.34%	10.68%

Notes: The table shows premia estimates for the BBGB model and CAPM. The test assets are the 25 *ME*- and *BE*/*ME*-sorted portfolios and 20 risk-sorted portfolios. The second column uses the method one to do news decomposition, i.e., cash-flow news are discounted sum of roe for future 5 years and combined with a state-space model to separate the discount-rate news from the realized market returns, and we named it as "roe5+SSP". The third column uses the method two to construct two market news series, i.e., cash-flow news are discounted sum of roe for future 5 years and discount-rate news are discounted sum of P/E for future 5 years, and we named it as "roe5+P/E5". The CAPM is the standard Sharpe-Lintner static model. Estimates are from a cross-sectional regression of average simple excess test-asset returns (monthly in fractions) on an intercept and estimated cash-flow ($\hat{\boldsymbol{\beta}}_{\mathbf{CF}}$) and discount-rate betas ($\hat{\boldsymbol{\beta}}_{\mathbf{DR}}$). Standard errors are in the parentheses. Estimates are for the 1973:09-2006:01 period.

Table 3 Asset Pricing Tests for 44 Cross-section Portfolios: 1973:09-2006:01

Model	**BBGB**	**BBGB**	**CAPM**
Method	[roe5+SSP]	[roe5+P/E5]	[standard]
Intercept (g_0)	0.0069	0.0090	0.0048
% per annum	8.33%	10.75%	5.71%
Std.err.	(0.0000)	(0.0000)	(0.0000)
$\hat{\beta}_{CF}$ premium (g_1)	0.0276	0.0203	
% per annum	33.08%	24.40%	
Std.err.	(0.0000)	(0.0000)	
$\hat{\beta}_{DR}$ premium (g_2)	0.0021	0.0013	
% per annum	2.57%	1.56%	
$\hat{\beta}_{CAPM}$ premium (g_3)			0.0041
% per annum			4.86%
Std.err.			(0.0000)
$\hat{R}^2$	29.54%	23.10%	18.67%

Notes: The table shows premia estimates for the BBGB model and CAPM. The test assets are the 24 *ME*- and *BE*/*ME*-sorted portfolios (the first small-growth portfolio excluded) and 20 risk-sorted portfolios. The second column uses the method one to do news decomposition, i.e., cash-flow news are discounted sum of roe for future 5 years and combined with a state-space model to separate the discount-rate news from the realized market returns, and we named it as "roe5+SSP". The third column uses the method two to construct two market news series, i.e., cash-flow news are discounted sum of roe for future 5 years and discount-rate news are discounted sum of P/E for future 5 years, and we named it as "roe5+P/E5". The CAPM is the standard Sharpe-Lintner static model. Estimates are from a cross-sectional regression of average simple excess test-asset returns (monthly in fractions) on an intercept and estimated cash-flow ($\hat{\boldsymbol{\beta}}_{\mathbf{CF}}$) and discount-rate betas ($\hat{\boldsymbol{\beta}}_{\mathbf{DR}}$). Standard errors are in the parentheses. Estimates are for the 1973:09-2006:01 period.

Table 4 Betas for 25 ME- and BE/ME- sorted portfolios (roe+SSP)

$\hat{\boldsymbol{\beta}}_{\mathbf{CF}}$	**Growth**	**2**	**3**	**4**	**Value**

Small	0.0338	0.0286	0.0249	0.0436	0.0621
2	0.0209	-0.0321	-0.0138	-0.0087	-0.0126
3	-0.0261	-0.0324	0.0019	-0.0261	-0.0138
4	-0.033	0.0082	0.004	-0.0001	-0.0658
Large	-0.0687	-0.0368	-0.0168	-0.0422	-0.0763
Diff.(S-L)	0.1025	0.0654	0.0417	0.0858	0.1384
$\hat{\boldsymbol{\beta}}_{\mathbf{DR}}$	**Growth**	**2**	**3**	**4**	**Value**
Small	1.6873	1.3876	1.1954	1.1129	1.189
2	1.5294	1.313	1.1363	1.0643	1.1787
3	1.4342	1.2077	1.0168	0.984	1.065
4	1.3424	1.1092	1.0239	0.9137	1.023
Large	1.1031	1.0217	0.8769	0.806	0.9278
Diff.(S-L)	0.5842	0.3659	0.3185	0.3069	0.2612

Notes: The table shows the estimated cash-flow ($\hat{\boldsymbol{\beta}}_{\mathbf{CF}}$) and discount-rate betas ($\hat{\boldsymbol{\beta}}_{\mathbf{DR}}$) for the 25 *ME*- and *BE*/*ME*-sorted portfolios. We use the method one to construct two market news series, i.e. cash-flow news are discounted sum of roe for future 5 years and combined with a state-space model to separate the discount-rate news from the realized market returns. Diff.(S-L) denotes the β difference between small portfolios and large portfolios. Estimates are for the 1973:09-2006:01 period.

Table 5 Betas for 25 ME- and BE/ME- sorted portfolios (roe+P/E)

$\hat{\boldsymbol{\beta}}_{\mathbf{CF}}$	**Growth**	**2**	**3**	**4**	**Value**
Small	0.0557	0.0471	0.041	0.0718	0.1022
2	0.0344	-0.0528	-0.0227	-0.0143	-0.0207
3	-0.0428	-0.0532	0.0032	-0.043	-0.0227
4	-0.0542	0.0134	0.0065	-0.0001	-0.1082
Large	-0.1129	-0.0605	-0.0277	-0.0696	-0.1256
Diff.(S-L)	0.1686	0.1076	0.0687	0.1414	0.2278
$\hat{\boldsymbol{\beta}}_{\mathbf{DR}}$	**Growth**	**2**	**3**	**4**	**Value**
Small	0.1232	0.1753	0.1599	0.1547	0.1878
2	0.2868	0.266	0.2778	0.2682	0.2226
3	0.4095	0.3006	0.2555	0.2792	0.2174
4	0.3428	0.2516	0.2329	0.1533	0.2284
Large	0.3735	0.3037	0.2254	0.2599	0.2812
Diff.(S-L)	-0.2503	-0.1284	-0.0655	-0.1052	-0.0934

Notes: The table shows the estimated cash-flow ($\hat{\boldsymbol{\beta}}_{\mathbf{CF}}$) and discount-rate betas ($\hat{\boldsymbol{\beta}}_{\mathbf{DR}}$) for the 25 *ME*- and *BE*/*ME*-sorted portfolios. We use the method two to construct two market news series, i.e., the cash-flow news are discounted sum of roe for future 5 years and the discount-rate news are discounted sum of P/E for future 5 years. Diff.(S-L) denotes the $\boldsymbol{\beta}$ difference between small portfolios and large portfolios. Estimates are for the 1973:09-2006:01 period.